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Evaluating the accuracy of VEMAP daily weather data for application in crop simulations on a regional scale

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ABSTRACT

Weather plays a critical role in eco-environmental and agricultural systems. Limited availability of meteorological records often constrains the applications of simulation models and related decision support tools. The Vegetation/Ecosystem Modeling and Analysis Project (VEMAP) provides daily weather variables on a 0.5 latitude–longitude grid across the conterminous USA. Daily weather data from the VEMAP (1961–1990) for the state of Georgia were compared with data from 52 individual ground stations of the National Weather Service Cooperative Observer Program (COOP). Additionally, simulated crop grain yields of soybean (*Glycine max*) were compared using the two data sources. Averaged daily maximum and minimum temperatures (Tmax and Tmin, respectively), solar radiation (SRAD), and precipitation (PPT) differed by 0.2 °C, −0.2 °C, 1.7 MJ m^{-2} d^{-1}, and 0 mm, respectively. Mean absolute errors (MAEs) for Tmax, Tmin, SRAD, and PPT were 4.2 °C, 4.4 °C, 4.4 MJ m^{-2} d^{-1}, and 6.1 mm, respectively, and root mean squared errors (RMSEs) for Tmax, Tmin, SRAD, and PPT were 5.5 °C, 5.9 °C, 5.8 MJ m^{-2} d^{-1}, and 13.6 mm, respectively. Temperature differences were lowest during summer months. Simulations of grain yield using the two data sources were strongly correlated (r = 0.68, p < 0.01). The MAE of grain yield was 552 kg ha^{-1}. The RMSE of grain yield was 714 kg ha^{-1}. Hybrid analyses indicated that the variation of simulated yield was mainly associated with the differences in rainfall. The results showed that the VEMAP daily weather data were able to be adequately applied to crop growth simulation at spatial and temporal scales, especially for long-term climate change research. Overall, the VEMAP weather data appears to be a promising source for crop growth modeling concerned with scale to 0.5° coordinate grid.

1. Introduction

Weather data are one of the most important input variables for biophysical and eco-environmental systems, as well as for agricultural production. For many of these applications, the availability of meteorological data at regional or national scale enables the weather-sensitive models to run at any desired geographical location. Usually, spatial interpolation is the first step in processing point data and converting it for use in ecosystem modeling at large scales.

Various different interpolation methods have been developed to model the spatial distribution of weather from point data. For example, thin-plate smoothing splines (e.g. Hutchinson, 1995; Wahba and Wendelberger, 1980; Cressie, 2003), Thiessen polygons (e.g. Thiessen, 1911; Shepard, 1968; Delfiner and Delhomme, 1973), inverse squared distance (e.g. Price et al., 2000; Xia et al., 1999, 2001), kriging (e.g. Bolstad et al., 1998; Couralt and Monestiez, 1999; Garen and Marks, 2005), inverse distance weighting (e.g. Supit, 1997; Van der Goot, 1998; Dodson and Marks, 1997; Shen et al., 2001) and trend surface analysis (e.g. Rossi et al., 1993; Goodale et al., 1998) have been employed to interpolate weather data for different regions. In addition, with respect to the impact of topographical and land cover on climatic conditions, some complicated approaches with multiple parameters were put forward, such as PRISM (Daly et al., 1997), DAYMET (Thornton et al., 1997) and ANUSPLIN (Hutchinson, 1995). From the view of interpolation, the next generation of interpolators will be those able to incorporate knowledge of the underlying climatological processes (Mitás and Mitásová, 1999). Comprehensive intercomparisons include Jarvis and Stuart (2001) and Daly (2006).

Recently, medium resolution daily weather datasets have become available at a continental or global scale. Most of them are inverted from satellites based on different methods. For instance, the Prediction of Worldwide Energy Resources (NOAA/POWER)

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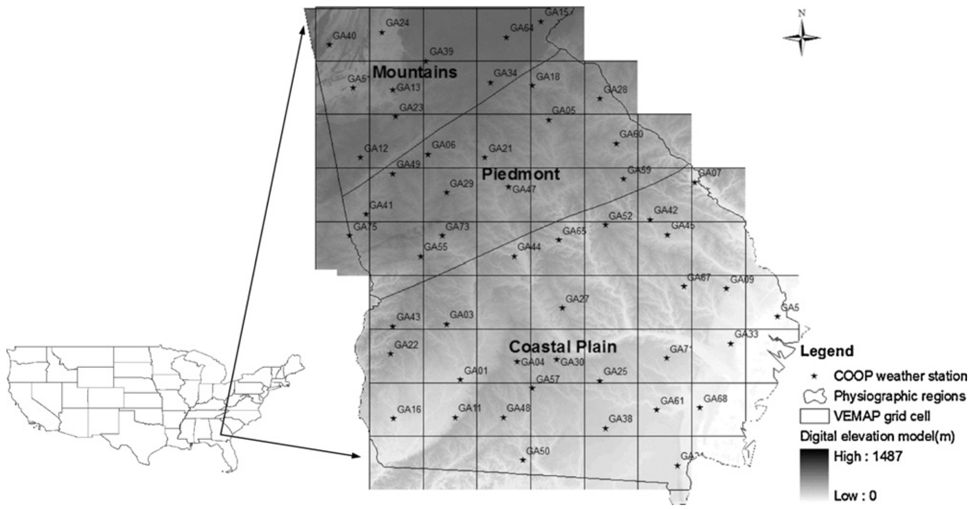

Fig. 1. Location of the study site. Digital elevation model (DEM) of Georgia. The distribution of the COOP weather stations. The VEMAP grid cell and the three physiography regions.

database (http://power.larc.nasa.gov) contains daily data for precipitation, solar radiation, maximum and minimum temperatures, and other weather variables on a 1° geographic coordinate grid for the entire globe using Goddard Earth Observing System (GEOS) assimilation model, Version 4 (Bloom et al., 2005; Stackhouse, 2006). However, satellite data are unavailable for dates before the 1970s. Compared to the NOAA/POWER datasets, the Vegetation/Ecosystem Modeling and Analysis Project (VEMAP) has a finer resolution (0.5° latitude/longitude grid) for daily weather data across the conterminous USA (VEMAP, 1995) based on spatial interpolation of observed data. The VEMAP files are accessible from the Internet (http://www.cgd.ucar.edu/vemap/). A number of studies evaluated the response of regional or national ecosystems and agricultural production to a changing climate using the VEMAP database (e.g. VEMAP, 1995; Pan et al., 1998; Loáiciga et al., 2000; Rosenberg et al., 2003; Coops et al., 2005; Coulson and Joyce, 2006; Southworth et al., 2000; O'Neal et al., 2005; Dhungana et al., 2006).

Crop growth is strongly influenced by weather conditions. In recent decades, quantitative crop growth modeling approaches have seen increasing use (e.g. de Wit et al., 1970; Jones et al., 2003; Hoogenboom et al., 2004; Stöckle et al., 2003). These models often simulate crop growth and development with a daily time interval, and accurate weather data are indispensable. Since there is an increasing demand to run the crop growth models at the regional or national scale, one of the problems facing meteorologists and crop modeling users is the usefulness of public climate spatial datasets in crop simulation. For NOAA/POWER, White et al. (2008) assessed the utility of NASA/POWER daily temperatures from 1983 to 2006 in crop growth simulation application. For many areas, except in mountainous and coastal regions, the dataset could be a source of daily temperature data for research and management applications. Recently, studies such as Jagtap and Jones (2002) and Irmak et al. (2005) used the VEMAP databases to simulate soybean yield at a regional scale. They suggested that some adjusted factors should be used to correct the simulated yields when compared to county-level reported yields. However, the utility of the VEMAP daily weather database for simulation modeling remains unclear, especially for region scales. In the current paper, we assumed that there is no error in the records of the NOAA National Weather Service Cooperative Observes Program (COOP) data set. Therefore, the objectives of our study were to (1) investigate the accuracy of the VEMAP daily weather data by comparing those data with the COOP data on a regional scale and (2) examine the utility of the VEMAP daily weather application in crop simulation models by comparing simulated crop yields using the two sets of daily weather data.

2. Materials and methods

2.1. Study area

The state of Georgia, USA, was selected for this study because of its diverse physiography (mountains, piedmont, and costal plain) and the availability of long-term weather records. It is located in the southeastern part of the US (30°31′N to 35°N, 81°W to 85°53′W) (Fig. 1). The elevation ranges from 0 to 1487 m, with mean annual temperature ranging from 12.8 to 21.1 °C and mean annual rainfall ranging from 112 to 229 cm.

2.2. Data set and comparison

Daily weather variables selected for this study were: solar radiation, SRAD; precipitation, PPT; and maximum and minimum temperatures, Tmax and Tmin, respectively. Primarily, tow daily weather data sets were created. One included the VEMAP daily weather data which have been converted into a crop model-ready format (Wu et al., 2010). The second file containing the daily weather data from COOP stations were used as the basis of comparisons. COOP stations were initially geo-referenced and filtered for completeness of data, resulting in list of approximately 64 stations. Stations which were closest to the centroid of the corresponding VEMAP cells were checked, coded, and selected for analysis. In total, usable data from 52 stations were obtained (Fig. 1).

Soybean growth and development were simulated using the CROPGRO-Soybean model, which is integrated into the Decision Support System for Agrotechnology Transfer, Version 4.0.2.0 (DSSAT; Hoogenboom et al., 2004). The most dominant soil from the VEMAP soil dataset (VEMAP, 1995; Wu et al., 2010) and a high yielding cultivar from maturity group V with a row spacing of 0.91 m, a planting population of 27 plants m^{-2}, and planting date of May 10 were simulated on rainfed condition. The simulated period was from 1961 to 1990. Crop growth and development variable was grain yield at harvest maturity (yield).

Basic comparisons of the VEMAP and COOP daily weather data and of simulated crop growth data using root mean squared error (RMSE), mean absolute error (MAE), determination coefficient (r^2), and correlation coefficient (r). Statistical analyses were carried out in Statistics 6.0 (Statsoft, Inc.).

Table 1
Basic statistical analysis of the VEMAP grid and the COOP weather stations covering the state of Georgia, USA.

Variable	Data source	Mean	Min.	Max.
Elevation (m)	VEMAP	150	7	522
	COOP	167.1	14	573
	Difference between VEMAP and COOP	−17.1	−200	83
Distance from centroid (km)	16.4	2.9	34.3	

Elevation: mean value of grid cell for the VEMAP and the reported value for COOP station.

3. Results

3.1. Basic information on the VEMAP grid and the COOP station sites

Only one COOP station in Georgia (GA33) started recording weather data from 1964. The average elevation of the COOP weather stations was 167.1 m, ranging from 14 to 573 m, and 17.1 m higher than the VEMAP with a range from 7 to 522 m (Table 1). The difference in elevation between the VEMAP grid and the COOP weather stations varies from −200 to 83 m. The larger differences in elevation were found in the Piedmont and Mountain Region (Fig. 2(A)). The distance from the COOP weather station to the centroid of the corresponding VEMAP grid cell ranges from 2.9 to 34.3 km, averaging 16.4 km (Table 1 and Fig. 2(B)). The distribution of the differences in the distance was unevenly across Georgia (Fig. 2(B)).

3.2. Comparisons of daily weather data

Overall good agreement was found between the VEMAP and COOP data for Tmax, Tmin, SRAD, and PPT. However, there existed large discrepancies for single pairs of daily values (Fig. 3(A–D) and Table 2). The overall mean value of Tmax for the VEMAP was 0.2 °C warmer than the COOP data, values of Tmin averaged 0.2 °C cooler, and values of SRAD were approximately 1.7 MJ m^{-2} d^{-1} higher than the COOP data. For averaged PPT, no difference was found between the VEMAP and the COOP data.

To investigate whether the differences between the VEMAP and COOP data varied with season, the mean, MAE, and RSME of daily differences over all grid cells and stations were calculated and plotted in Fig. 4(A–D). For Tmax, mean value ranged from −1.9 to 2.5 °C, MAE from 2.5 to 6.9 °C, and RMSE from 3.2 to 8.5 °C. For Tmin, mean value ranged from −3.4 to 1.9 °C, MAE from 2 to 7.4 °C, and RMSE from 2.6 to 9.2 °C. For SRAD, mean value varied from −0.6 to 5.1 MJ m^{-2} d^{-1}, MAE from 2.8 to 6.6 MJ m^{-2} d^{-1}, and RSME from 3.6 to 8.4 MJ m^{-2} d^{-1}. For PPT, mean value ranged from −3.7 to 3.3 mm, MAE from 2.9 to 9.7 mm, and RMSE from 7.9 to 19.5 mm. It was obvious that the differences varied along with the season fluctuations (Fig. 4(A–D)). The difference in Tmax was about 1.0 °C from April to August, but widened to −2 to 2.5 °C from November to March. The difference in Tmin varied from −1.5 to 1.5 °C with a larger bias occurring from November to March. The difference in SRAD ranged from −0.6 to 5.1 MJ m^{-2} d^{-1}; the larger bias occurred from February to May. The mean difference in rainfall varied by over 2 mm, and widened to −3 to 3 mm from December to April.

The difference in elevation of the VEMAP and the COOP stations was significantly ($p < 0.01$) correlated with the differences in SRAD, Tmax, Tmin, and PPT ($r = 0.009$, −0.038, −0.048, and 0.007, respectively). Meanwhile, the distance from the COOP stations to the centroid of the VEMAP grid cells was significantly correlated ($p < 0.01$) with SRAD, Tmax, and Tmin ($r = 0.014$, 0.007, and −0.024, respectively) and positively correlated ($p > 0.05$) with PPT ($r = 0.0007$). These relationships indicated that discrepancies in daily weather data were partly due to differences between the elevations of the grid cells of the VEMAP data and of the COOP stations. In addition, the effect of the distance between the centroid of VEMAP grid cells and the corresponding COOP stations could not be ignored.

3.3. Comparisons of simulated grain yields

Simulation of grain yield using the two data sources confirmed that the overall agreement between the daily weather data sources

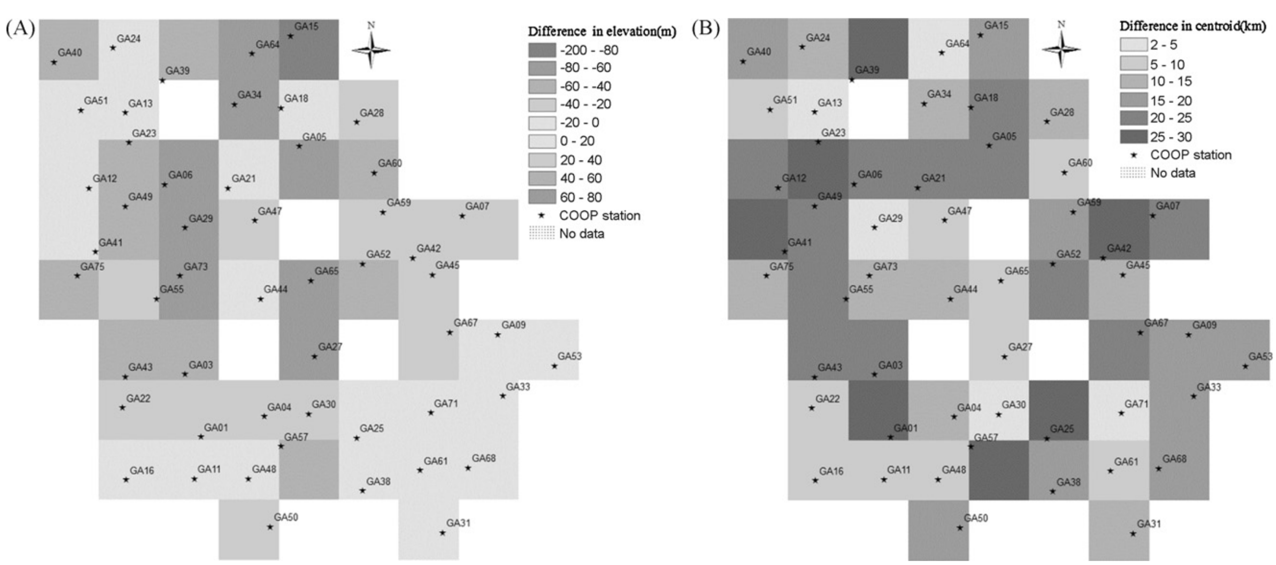

Fig. 2. Map of difference in elevation between the VEMAP data and the COOP weather station (A). Map of the distance between the COOP weather station and the VEMAP grid cell centroid (B).

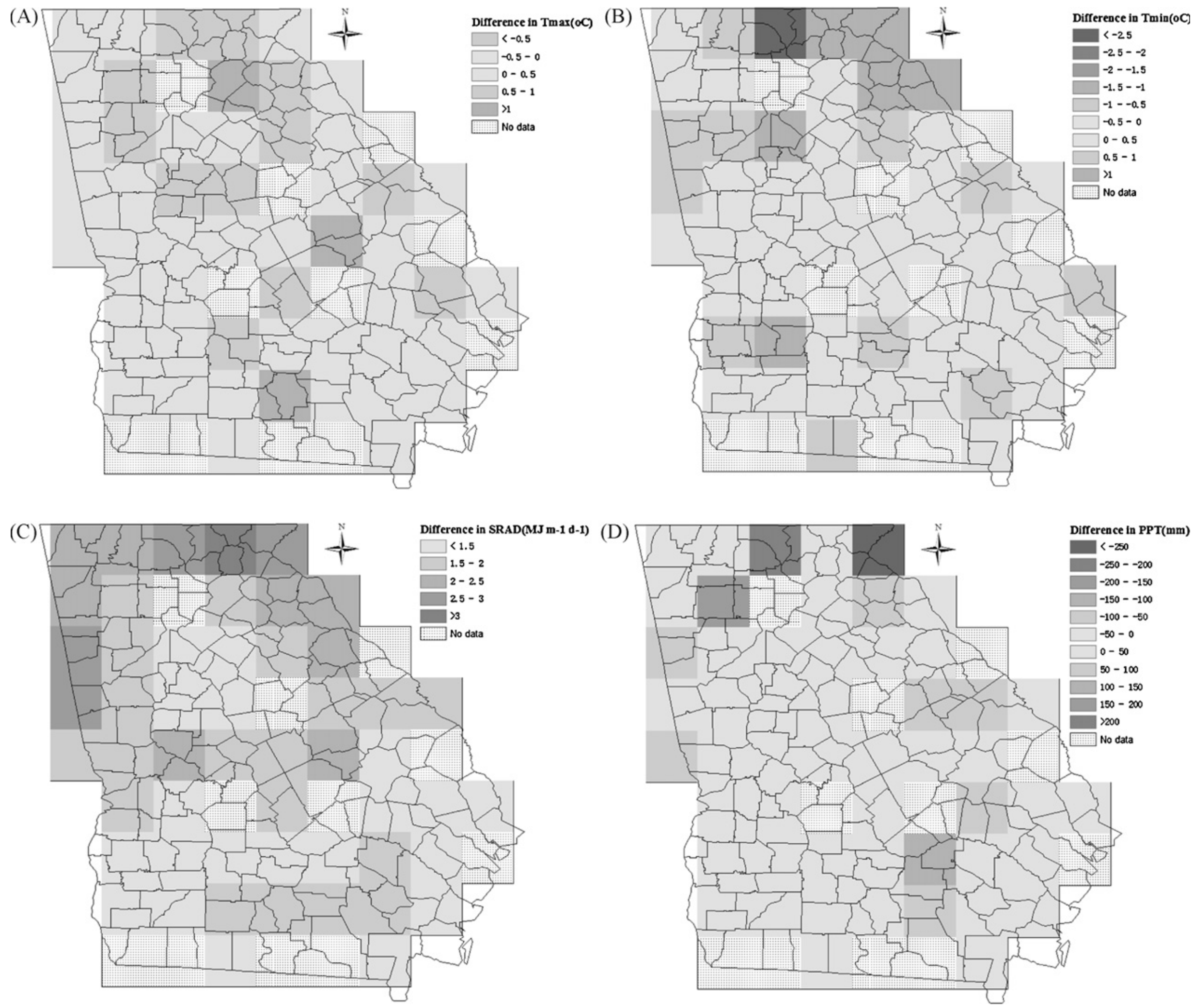

Fig. 3. Mean difference in daily weather data of VEMAP minus COOP data source for 1961–1990: (A) maximum temperature; (B) minimum temperature; (C) solar radiation; (D) rainfall.

would result in similar variation in crop growth and development (Table 3 and Fig. 5). The correlation coefficient of the simulated grain yield was 0.68 ($p < 0.01$). The RMSE was 714 kg ha^{-1}. For the long-term simulated grain yield, the correlation coefficient of 30-year mean simulated yields using the two daily weather data was 0.73 ($p < 0.01$) (Fig. 6).

3.4. Hybrid analyses

A hybrid analysis approach was employed to isolate the impact of daily weather parameters on crop models. Thus, four combination data sets were created, namely, CW1: VEMAP PPT and SRAD with COOP Tmax and Tmin; CW2: VEMAP PPT, Tmax, and

Table 2
Basic statistical analysis of VEMAP and COOP daily weather data for 52 locations on a half degree grid covering Georgia from 1961 to 1990.

Variable	Data source	Mean	Min.	Max.	MAE	RMSE
Tmax (°C)	VEMAP	24.0	−17.7	44.9		
	COOP	23.8	−16.5	42.9		
	Difference between VEMAP and COOP	0.2	−27.2	32.1	4.2	5.5
Tmin (°C)	VEMAP	10.5	−27.0	31.9		
	COOP	10.6	−25.3	33.0		
	Difference between VEMAP and COOP	−0.2	−34.5	32.7	4.4	5.9
SRAD (MJ m^{-2} d^{-1})	VEMAP	17.7	0.9	31.8		
	COOP	16.0	2.6	32.9		
	Difference between VEMAP and COOP	1.7	−23.7	24.6	4.4	5.8
Rainfall (mm)	VEMAP	3.6	0	208.4		
	COOP	3.6	0	264.2		
	Difference between VEMAP and COOP	0	−264.2	180.2	6.1	13.6

MAE: mean absolute error; RMSE: root mean squared error; Tmax: maximum temperature; Tmin: minimum temperature; SRAD: solar radiation.

Tmin with COOP SRAD; CW3: VEMAP Tmax, Tmin, and SRAD with COOP PPT; CW4: VEMAP Tmax and Tmin with COOP PPT and SRAD, respectively (Table 4). The comparisons of simulated grain yields using different sources by re-running the simulation model with the same soil, initial conditions and management practices were summarized in Table 5. Compared to other data sets, CW4 gave better performance with the slope, r^2, r, and RMSE of 0.98, 0.92, 0.96, and 266 kg ha^{-1}, respectively. The results suggested that the largest difference in simulated grain yields were due to the variation in precipitation, although it looked like the variation in solar radiation also contributed about 10% of the difference.

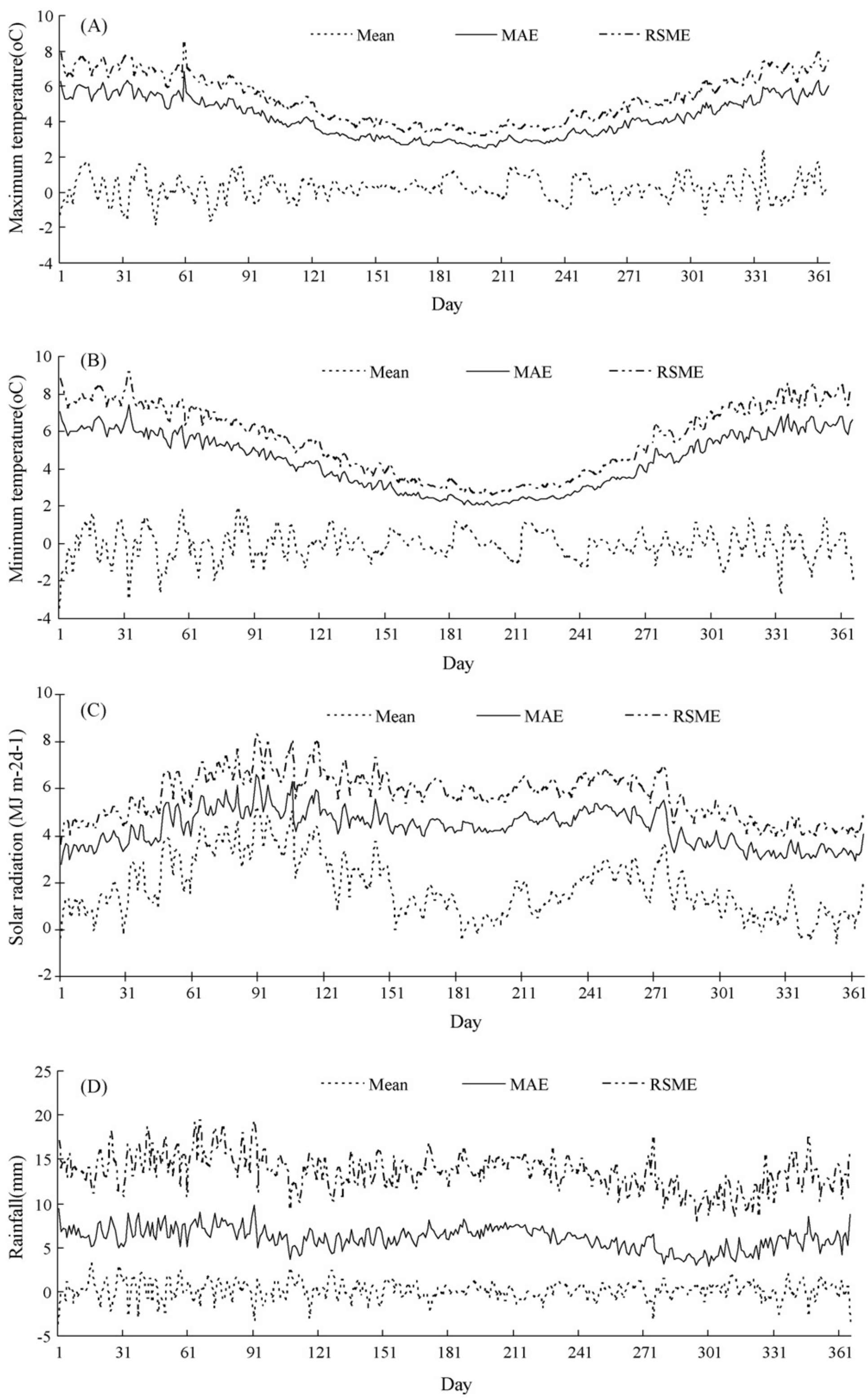

Fig. 4. Variation of mean, MAE, and RSME of the difference in daily weather data from VEMAP and COOP station in relation to time of year. (A) Maximum temperature; (B) minimum temperature; (C) solar radiation; (D) rainfall.

Table 3
Basic statistical analysis of simulated yield using VEMAP and COOP data for 52 locations on a half degree grid covering Georgia from 1961 to 1990.

Variable	Data source	Mean	Min.	Max.	MAE	RMSE
Yield (kg ha^{-1})	VEMAP	2349	130	3992		
	COOP	2483	155	3864		
	Difference between VEMAP and COOP	−134	−2743	2627	552	714

MAE: mean absolute error; RMSE: root mean squared error.

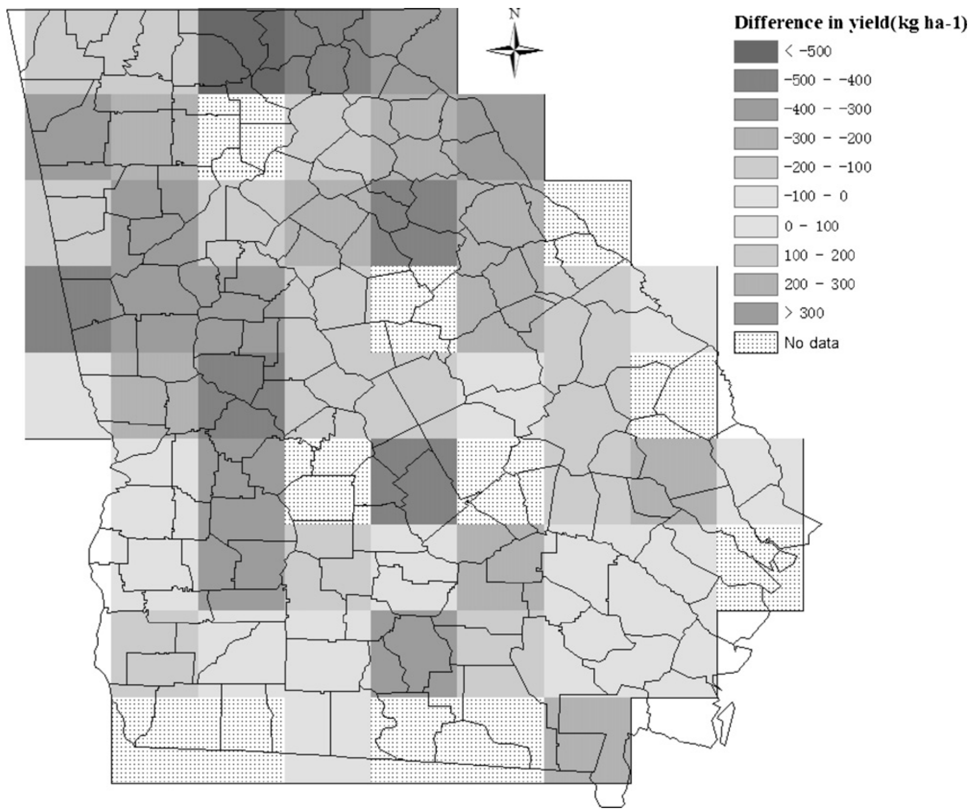

Fig. 5. Map of mean difference in simulation of grain yield for 1961–1990 using VEMAP and COOP data.

Table 4
Combined data sets using VEMAP and COOP weather for hybrid analysis.

Data set	Precipitation	Solar radiation	Maximum temperature	Minimum temperature
CW1	VEMAP	VEMAP	COOP	COOP
CW2	VEMAP	COOP	VEMAP	VEMAP
CW3	COOP	VEMAP	VEMAP	VEMAP
CW4	COOP	COOP	VEMAP	VEMAP

From the cumulative probability distributions, the grain yield with certain probability under different weather sources can be estimated (Fig. 7). Cumulative probability distributions of simulated grain yields under the VEMAP, COOP and CW3 daily weather sources were produced for each grid cell. Since it is impossible to show all graphs, the results of GA01 and GA30 were selected randomly and presented as examples (Fig. 7(A) and (B)). Median yield (with 50% probability of exceedance) was 2797, 2371, and 3013 kg ha^{-1} in GA01 under the COOP, VEMAP, and CW3 weather sources, respectively. Similarly, median yield was 2604, 2593, and 2230 kg ha^{-1} in GA30 under the COOP, VEMAP, and CW3 weather datasets, respectively. It is clearly, these results suggested that grain

Table 5
The relationships between the simulated grain yields using the VEMAP, combined weather files and the COOP daily weather.

Source	Mean (kg ha^{-1})	Slope	r^2	r	RMSE (kg ha^{-1})
COOP vs. VEMAP	134	0.71	0.46**	0.68**	714
COOP vs. CW1	32	0.74	0.49**	0.70**	675
COOP vs. CW2	−64	0.64	0.50**	0.71**	634
COOP vs. CW3	255	1.04	0.82**	0.91**	494
COOP vs. CW4	83	0.98	0.92**	0.96**	266

CW1, CW2, CW3, and CW4 see Table 4. Mean: average of difference in the simulated grain yields using the corresponding weather data; RMSE: root mean squared error.
** 0.01 significant level.

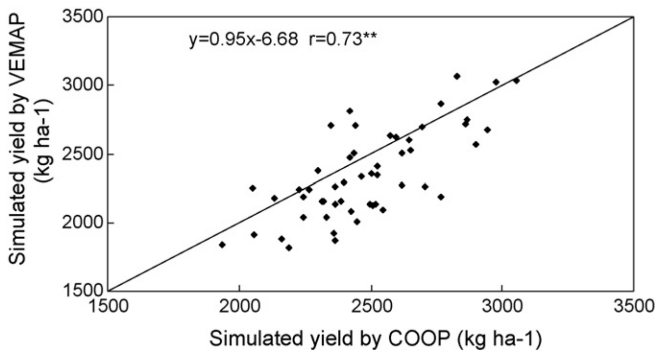

Fig. 6. Relationship between mean value of 30-year simulated grain yield using the VEMAP and COOP daily weather over 52 grid cells.

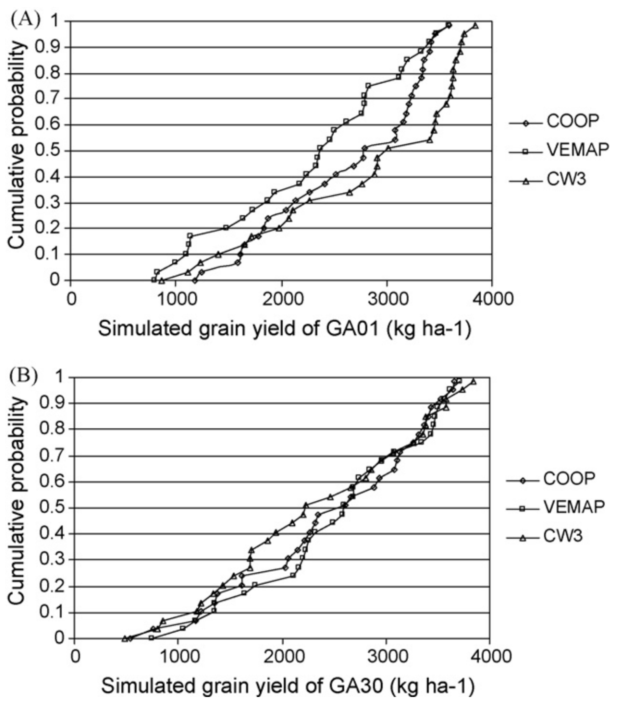

Fig. 7. Cumulative probability of simulated grain yields in GA01 (A) and GA30 (B) for 1961–1990 using VEMAP, COOP and combination weather data. CW3 represents the daily weather data which combined VEMAP maximum and minimum temperature, solar radiation with COOP precipitation.

yield probability curves based on the VEMAP daily weather data exhibited the similar year-to-year variability as the COOP weather did.

4. Discussion

Overall, the results demonstrated that the VEMAP daily weather data were able to be adequately applied to crop growth simulation at spatial and temporal scales, especially for long-term climate change research, although the VEMAP daily weather data were stochastically generated with WGEN (Richardson and Wright, 1984) and MTCLIM (Thornton and Running, 1999).

The detailed comparisons and hybrid analyses indicated that variability and uncertainty existed in the VEMAP daily weather database and it changed with the physiographic regions and seasonal fluctuation. The variation of simulated yield was mainly associated with the differences in rainfall. The largest discrepancy was found in mountainous areas on spatial and temporal scales (Figs. 1, 3 and 5).

In general, accurate estimation of the spatial distribution of meteorological data from point measurements over large areas is complicated, especially at continent or national scale. Price et al. (2000) applied Gradient plus Inverse-Distance-Squared (GIDS) and thin-plate smoothing splines (ANUSPLIN) to create 30-year monthly mean minimum and maximum temperature and precipitation maps for western and eastern Canada. The comparison revealed that both approaches performed best in the eastern region where topographic and climatic gradients are smoother, whereas predicting precipitation in the west was most difficult. For rainfall has much higher spatial and temporal variability than other weather variables. Additionally, the accuracy of spatial interpolation will usually be lower in areas of low weather station density. This is especially true in mountainous environments where the large variability in altitude, slope and aspect may increase variability in weather processes. The best method to improve the quality of spatial weather estimation is to increase the density of the monitoring network (e.g. Stahl et al., 2006; Dodson and Marks, 1997; Thornton et al., 1997; Garen and Marks, 2005; Hasenauer et al., 2003). For example, Stahl et al. (2006) reported that a greater number of higher-elevation stations allowed for higher accuracy estimation in complex topographic areas. However, this is very costly, and in many cases practically unfeasible.

Given that the VEMAP daily weather data are publicly available and provide a continuous daily record from 1895 to 1993 and a simulated period from 1994 to 2100, they represent a potentially valuable source for research and management applications concerned with spatial and temporal scales. Further analyses will focus on (1) introducing correction factors for the bias between simulated and census yield by taking into account physiographic differences and (2) using the VEMAP data to simulate the crop growth and development with respect to climate changing.

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References

Bloom, S., da Silva, A., Dee, D., Bosilovich, M., Chern, J.D., Pawson, S., Schubert, S., Sienkiewicz, M., Stajner, I., Tan, W.W., Wu, M.L., 2005. Documentation and Validation of the Goddard Earth Observing System (GEOS) Data Assimilation System, Version 4. Technical Report Series on Global Modeling and Data Assimilation. NASA/TM-2005-104606, vol. 26.

Bolstad, P.V., Swift, L., Collins, F., Régnière, J., 1998. Measured and predicted air temperatures at basin to regional scales in the southern Appalachian. Agric. Forest Meteorol. 91, 161–178.

Coops, N.C., Waring, R.H., Law, B.E., 2005. Assessing the past and future distribution and productivity of ponderosa pine in the Pacific Northwest using a process model, 3-PG. Ecol. Model. 183, 107–124.

Coulson, D., Joyce, L., 2006. Indexing variability: a case study with climate change impacts on ecosystems. Ecol. Indic. 6, 749–769.

Couralt, D., Monestiez, P., 1999. Spatial interpolation of air temperature according to atmospheric circulation patterns in southeast France. Int. J. Climatol. 19, 365–378.

Cressie, N., 2003. Statistics for Spatial Data, Revised ed. John Wiley and Sons, New York.

de Wit, C.T., Brouwer, R., Penning de Vries, F.W.T., 1970. The simulation of photosynthetic systems. In: Setlik, I. (Ed.), Prediction and Measurement of Photosynthetic Productivity. Proceeding IBP/PP Technical Meeting Trebon 1969. Pudoc, Wageningen, The Netherlands, pp. 47–50.

Daly, C., Taylor, G., Gibson, W., 1997. The PRISM approach to mapping precipitation and temperature. In: Proc., 10th AMS Conf. on Appl. Climatology, American Meteorological Society, Boston, MA.

Daly, C., 2006. Guidelines for assessing the suitability of spatial climate data sets. Int. J. Climatol. 26, 707–721.

Delfiner, P., Delhomme, J.P., 1973. Optimum interpolation by kriging. In: Davies, J.C., McCullagh, M.J. (Eds.), Display and Analysis of Spatial Data. John Wiley and Sons, New York, pp. 96–114.
Dhungana, P., Eskridge, K.M., Weiss, A., Baenziger, P.S., 2006. Designing crop technology for a future climate: an example using response surface methodology and the CERES-Wheat model. Agric. Syst. 87, 63–79.
Dodson, R., Marks, D., 1997. Daily air temperature interpolated at high spatial resolution over a large mountainous region. Climate Res. 8, 1–20.
Garen, D.C., Marks, D., 2005. Spatially distributed energy balance snowmelt modelling in a mountainous river basin: estimation of meteorological inputs and verification of model results. J. Hydrol. 315, 126–153.
Goodale, C., Aber, J., Ollinger, S., 1998. Mapping monthly precipitation, temperature, and solar radiation for Ireland with polynomial regression and a digital elevation model. Climate Res. 10, 35–49.
Hasenauer, H., Merganicova, K., Petritsch, R., Pietsch, S.A., Thornton, P.E., 2003. Validation of daily climate interpolations over complex terrain in Austria. Agric. Forest Meteorol. 119, 87–107.
Hoogenboom, G., Jones, J.W., Wilkens, P.W., Porter, C.H., Batchelor, W.D., Hunt, L.A., Boote, K.J., Singh, U., Uryasev, O., Bowen, W.T., Gijsman, A.J., du Toit, A., White, J.W., Tsuji, G.Y., 2004. Decision Support System for Agrotechnology Transfer Version 4.0 [CD-ROM]. University of Hawaii, Honolulu, Hawaii.
Hutchinson, M.F., 1995. Interpolating mean rainfall using thin plate smoothing splines. Int. J. Geogr. Inf. Syst. 9, 385–403.
Irmak, A., Jones, J.W., Jagtap, S.S., 2005. Evaluation of the CROPGRO-Soybean model for assessing climate impacts on regional soybean yields. Trans. ASAE 48, 2343–2353.
Jagtap, S.S., Jones, J.W., 2002. Adaptation and evaluation of the CROPGRO- soybean model to predict regional yield and production. Agric. Ecosyst. Environ. 93, 73–85.
Jarvis, C.H., Stuart, N., 2001. A comparison among strategies for interpolating maximum and minimum daily air temperatures. Part II. The interaction between number of guiding variables and the type of interpolation method. J. Appl. Meteorol. 40, 1075–1084.
Jones, J.W., Hoogenboom, G., Porter, C.H., Boote, K.J., Batchelor, W.D., Hunt, L.A., Wilkens, P.W., Singh, U., Gijsman, A.J., Ritchie, J.T., 2003. The DSSAT cropping system model. Eur. J. Agron. 18, 235–265.
Loáiciga, H.A., Maidment, D.R., Valdes, J.B., 2000. Climate-change impacts in a regional karst aquifer, Texas, USA. J. Hydrol. 227, 173–194.
Mitás, L., Mitásová, H., 1999. Spatial interpolation. In: Longley, P., Goodchild, M.F., Maguire, D.J., Rhind, D.W. (Eds.), Geographical Information Systems: Principles, Techniques, Management and Application, 2nd ed. Wiley, pp. 481–492.
O'Neal, M.R., Nearing, M.A., Vining, R.C., Southworth, J., Pfeifer, R.A., 2005. Climate change impacts on soil erosion in Midwest United States with changes in crop management. Catena 61, 165–184.
Pan, Y., Melillo, J.M., McGuire, A.D., Kicklighter, D.W., Pitelka, L., VEMAP Members, 1998. Modeled response of terrestrial ecosystems to elevated atmospheric CO_2: a comparison of simulation studies among biogeochemistry models. Oecologia 114, 389–404.
Price, D.T., McKenny, D.W., Nalder, I.A., Hutchinson, M.F., Kesteven, J.L., 2000. A comparison of two statistical methods for spatial interpolation of Canadian monthly mean climate data. Agric. Forest Meteorol. 101, 81–94.
Richardson, C.W., Wright, D.A., 1984. A Model for Generating Daily Weather Variables. ARS-8. U.S. Department of Agriculture, Agricultural Research Service, 83 pp.
Rosenberg, N.J., Brown, R.A., Izaurralde, R.C., Thomson, A.M., 2003. Integrated assessment of Hadley Centre (HadCM2) climate change projections on agricultural productivity and irrigation water supply in the conterminous United States. I. Climate change scenarios and impacts on irrigation water supply simulated with the HUMUS model. Agric. Forest Meteorol. 117, 73–96.
Rossi, R.E., Borth, P.W., Tollefson, J.J., 1993. Stochastic simulation for characterizing ecological spatial patterns and appraising risk. Ecol. Appl. 3, 719–735.
Shen, S.S.P., Dzikowski, P., Li, G.L., Griffith, D., 2001. Interpolation of 1961–1997 daily temperature and precipitation data onto Alberta polygons of ecodistrict and soil landscapes of Canada. J. Appl. Meteorol. 40, 2162–2177.
Shepard, D.L., 1968. A two dimensional interpolation function for irregularly spaced data. In: Proc. 23rd Nat. Conf. Assoc. Computing Machinery, ACM, Washington, pp. 517–524.
Southworth, J., Randolph, J.C., Habeck, M., Doering, O.C., 2000. Consequences of future climate change and changing climate variability on maize yields in the Midwestern United States. Agric. Ecosyst. Environ. 82, 139–158.
Stackhouse, P., 2006. Prediction of Worldwide Energy Resources. http://power.larc.nasa.gov (verified March 24, 2998).
Stahl, K., Moore, R.D., Floyer, J.A., Asplin, M.G., McKendry, I.G., 2006. Comparison of approaches for spatial interpolation of daily air temperature in a large region with complex topography and highly variable station density. Agric. Forest Meteorol. 139, 224–236.
Stöckle, C.O., Donatelli, M., Nelson, R., 2003. CropSyst, a cropping systems simulation model. Eur. J. Agron. 18, 289–307.
Supit, I., 1997. Predicting national wheat yields using a crop simulation and trend models. Agric. Forest Meteorol. 88, 199–214.
Thiessen, A.H., 1911. Precipitation averages for large areas. Mon. Weather Rev. 39, 1082–1084.
Thornton, P.E., Running, S.W., White, M.A., 1997. Generating surfaces of daily meteorological variables over large regions of complex terrain. J. Hydrol. 190, 214–251.
Thornton, P.E., Running, S.W., 1999. An improved algorithm for estimating incident daily solar radiation from measurements of temperature, humidity, and precipitation. Agric. Forest Meteorol. 93, 211–228.
Van der Goot, E., 1998. Spatial interpolation of daily meteorological data for the crop growth monitoring system (CGMS). In: Proc. Data Spatial Distribution in Meteorology and Climatology, Volterra, Italy, Office for the Official Publications of the European Communities, pp. 141–154.
VEMAP Members, 1995. Vegetation/ecosystem modeling and analysis project: comparing biogeography and biogeochemistry models in a continental-scale study of terrestrial ecosystem responses to climate change and CO_2 doubling. Global Biogeochem. Cycle 9, 407–437.
Wahba, G., Wendelberger, J., 1980. Some new mathematical methods for variational objective analysis using splines and cross validation. Mon. Weather Rev. 108, 1122–1143.
White, J.W., Hoogenboom, G., Stackhouse Jr., P.W., Hoell, J.M., 2008. Evaluation of NASA satellite- and assimilation model-derived long-term daily temperature data over the continental US. Agric. Forest Meteorol. 148, 1574–1584.
Wu, W., Chen, J.L., Liu, H.B., Garcia y Garcia, A., Hoogenboom, G., 2010. Parameterizing soil and weather inputs for crop simulation models using the VEMAP database. Agric. Ecosyst. Environ. 135, 111–118.
Xia, Y., Winterhalter, M., Fabian, P., 1999. A model to interpolation monthly mean climatological data at Bavarian forest climate stations. Theor. Appl. Climatol. 64, 27–38.
Xia, Y., Fabian, P., Winterhalter, M., Zhao, M., 2001. Forest climatology: estimation and use of daily climatological data for Bavaria, Germany. Agric. Forest Meteorol. 106, 87–103.